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New improved hybrid MPPT based on neural network-model predictive control-Kalman filter for photovoltaic system

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ABSTRACT

In this paper, new hybrid maximum power point tracking (MPPT) strategy for Photovoltaic Systems has been proposed. The proposed technique for MPPT control based on a novel combination of an artificial neural network (ANN) with an improved model predictive control using kalman filter (NN-MPC-KF). In this paper the Kalman filter is used to estimate the converter state vector for minimized the cost function then predict the future value to track the maximum power point (MPP) with fast changing weather parameters. The proposed control technique can track the MPP in fast changing irradiance conditions and a small overshoot. Finally, the system is simulated in the MATLAB/Simulink environment. Several tests under stable and variable environmental conditions are made for the four algorithms, and results show a better performance of the proposed MPPT compared to conventional Perturb and Observation (P&O), neural network based proprtional integral control (NN-PI) and Neural Network based model predictive control (NN-MPC) in terms of response time, efficiency and steady-state oscillations.

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1. INTRODUCTION

Nowadays, the photovoltaic (PV) energy systems have an important position within the renewable energy sources [1]. The PV systems are described as power generation systems that convert solar irradiance into electrical energy. However, the PV system presented some limit to exploit the available power which is depends climatic conditions. Therefore, control techniques become very important task for harnessing the maximum energy. An efficient maximum power point tracking (MPPT) algorithm plays an importance role to harvest optimal available power.

Several techniques of maximum power point (MPP) extraction have been proposed in the literature [2-13]. However, some MPPT control method present drawbacks, like unability to respond accurately under rapid environmental changes and poor tracking of MPP. Therefore, to resolve this problem, a powerful method to predict the new position of MPP under rapid environmental changes must be used. In this context, many researches have estimated the MPP by artificial neural networks (ANN) method which is exploited for optimization, and prediction of performance of system [14]. The artificial neural networks do not need the mathematical model of the controlling process, being it is simple to understand and can offer good performance during the variation in operating conditions. In [15] the authors used the combined neural network (NN) with genetic algorithm (GA) and with modified perturb and observe (P&O) in PV system in [16]. In [17], the neural network is considered to estimate (V_{MPP}) in a stand-alone PV system. An implementation of a neural network inverse model controller for tracking the MPPT in PV module was discussed in [18].

In addition to the problem of tracking the maximum power point, optimizing converters efficiency is another important problem which attracts many researchers. Some of them have proposed control methods to increase the efficiency of converters such as a PID controller, fuzzy controller, sliding mode controller (SMC) and model predictive controller (MPC) [19-23]. The model predictive controller (MPC) scheme is presented in [24] in order to track the maximum power PV point; the results show that MPC technique gives better performance than conventional methods. Furthermore, hybrid MPC control methods increase the sensitivity [25].

For this purpose, many algorithms are combined with MPPT algorithm to obtain hybrid structure where the voltage or current values at the MPP are usually derived from the MPPT algorithm, and then it is used as a reference for MPC [26]. In [27], the Fuzzy Logic Controller based MPPT is proposed to track the MPP under variable climate conditions in order to improve the efficiency of the overall PV system. Neural fuzzy is presented in [28-30] in order to control the output voltage of the PV system who allows system to operate at maximum power point despite the temperature and irradiation changes.

Considering all issues summarized above, this study is focused on improving the control method dynamic capability. For this purpose, a novel combination of an Artificial Neural Network with an improved Model Predictive Control using Kalman Filter (NN-MPC-KF) is presented. The hybrid model-based MPPT algorithm proposed is based on the P-V curve and solar parameters include temperature and solar irradiance is used as input parameters. The maximum power point is tracked by Neural-Network in order to approximate current at MPP of the PV in different conditions. Moreover, MPC is used to maximize boost converter efficiency and Kalman Filter is used to estimate the converter state vector for minimizes the cost function then predict the future value to track the Maximum Power Point (MPP) with fast changing weather parameters.

This paper is structured as follows: In section 2, Photovoltaic method and its characteristics are described. The proposed method is illustrated in section 3. Section 4 summarized the simulation and results. Finally, an appropriate conclusion and future work are pointed out in section 5.

2. OVERALL SYSTEM CONFIGURATION

The synoptic schematic of the studied system is presented in Figure 1. The schematic consists of the main following components: PV system, DC-DC converter, MPPT algorithm and a resistive load. The proposed algorithm output is the reference current value which is then fed to a predictive controller. Then, the Kalman filter estimate the converter state vector for minimizes the cost function then predict the future value to track the maximum power point (MPP). The whole proposed strategy is used to control the DC-DC boost converter placed between the PV module and the load.

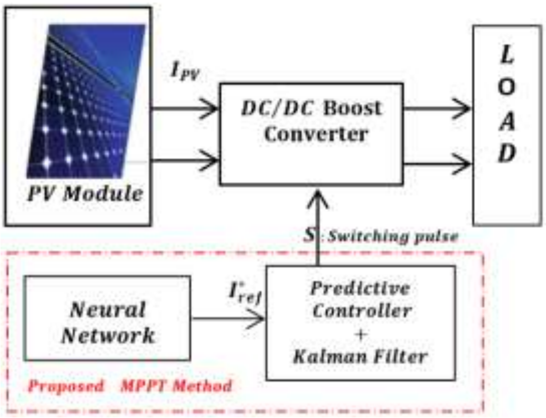


Figure 1. PV system with hybrid MPPT

2.1. Modeling of solar PV array

The photovoltaic cells use a $P\text{–}N$ junction semiconductor to absorb light energy and convert directly to electrical energy. In literature different mathematical model have been proposed for representation of photovoltaic cells, among of them a single diode model [31]. In this paper one diode has been adopted in the following analysis. Figure 2 shows the one-diode equivalent circuit used to obtain the model of PV cell.

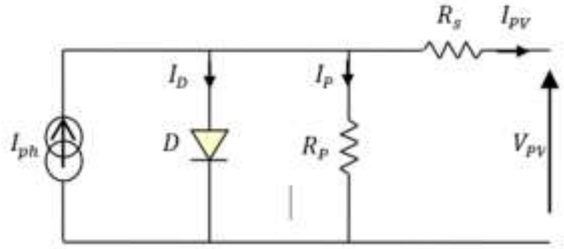


Figure 2. Circuit of photovoltaic cell

The diode current is given by:

$$I_D = I_0 \left(e^{\frac{q\,(V_{PV} + R_s\, I_{PV})}{AKT}} - 1\right) \tag{1}$$

$$\text{With} : I_0 = \left(\frac{V_{PV} + R_s\, I_{PV}}{R_P}\right) \tag{2}$$

The current generated by the PV cell is given by (4):

$$I_{PV} = I_{ph} - I_D - I_0 \tag{3}$$

$$I_{PV} = I_{ph} - I_0 \left(e^{\frac{q\,(V_{PV}+R_s\, I_{PV})}{AKT}} - 1\right) - \left(\frac{V_{PV} + R_s\, I_{PV}}{R_P}\right) \tag{4}$$

The photocurrent I_{ph} is linearly related to the irradiance level and to the temperature of the cell, and is given by the following equation [32]:

$$I_{ph} = \left[I_{Ph,n} + K_i(T - T_n)\right]\left(\frac{G}{G_n}\right) \tag{5}$$

where, K_i is the short circuit current/temperature coefficient(A/K), G is the value of solar irradiation (W/m^2) and T is the temperature (K).

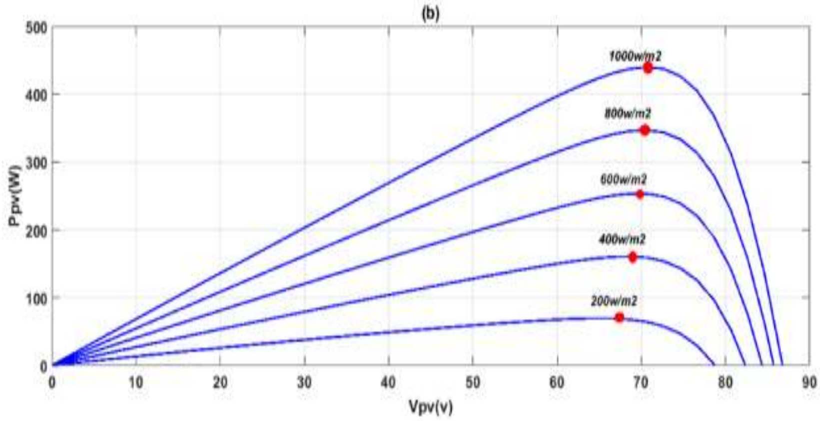
The photovoltaic array is composed to connection series or parallel of several photovoltaic cells. The mathematical representation of characterizing $I - V$ characteristics of PV array composed of N_s series and N_P parallel connected modules is given in (6) [20].

$$I_{PV} = N_P I_{ph} - N_P I_0 \left(e^{\frac{q\left(V_{PV}+R_S \frac{N_S}{N_p} I_{PV}\right)}{AKTN_S}} - 1\right) - \left(\frac{V_{PV} + R_S \frac{N_S}{N_p} I_{PV}}{R_P \frac{N_S}{N_p}}\right) \tag{6}$$

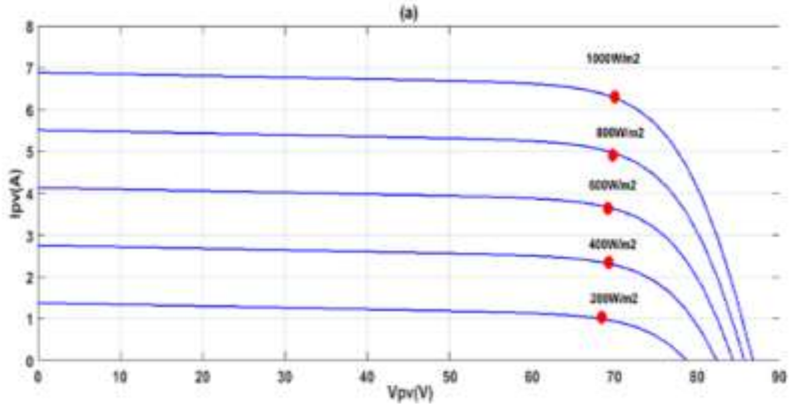
where:

I_{PV}, I_0 : are current supplied by the cell (A) and saturation current of the diode respectively.
q, K : are Electron charge and Boltzmann constant respectively.
T, A : are cell temperature in $Kelvin$ and Ideality coefficient of the PV cell respectively.
I_{ph} : Photo generated current by the PV cell under given illumination (A).
R_s,R_P : are series and parallel resistance of the cell (Ω).
N_s,N_p : Number of cells in series and parallel.

In Figure 3, the $V_{PV} = f(P_{PV})$ and $V_{PV} = f(I_{PV})$ PV characteristics for different irradiation levels are shown.



(a)



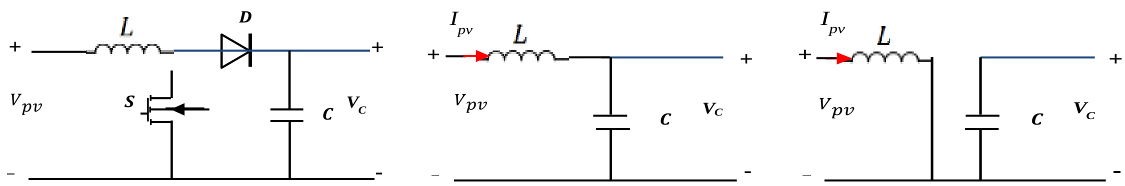
(b)

Figure 3. Characteristics of the PV array for different Irradiance levels:
(a) Power-Voltage (b) Current-Voltage

At the most time, the principal problem with photovoltaic systems is low efficiency because the MPP depends on different irradiance and temperature. Therefore, it is very important to ensure that the PV module operates at his maximum efficiency [33]. In order to overcome this problem, the MPPT is attained by interposing a DC–DC boost converter between the PV array and the load.

2.2. DC/DC boost converter

In this paper, the PV panel is coupled directly to a boost converter, used to realize the $MPPT$ operation with a resistive load. The boost converter topology is used to provide high voltage gain to achieve the maximum power by $MPPT$ algorithm [34]. The boost converter can be analyzed according to two possible swich states, diagrams of which are presented in Figure 4(b) and (c), separately. The $MPPT$ algorithm uses inputs measurements in order to generate the output current reference of the PV. Then, the controller of predictive current is aimed to regulate the PV current according to the reference current.



(a) (b) (c)

Figure 4. Boost converter equivalent circuits for the two switch states:
(a) Structure of boost circuit, (b) The switch is ON ($S = 1$), (c) The switch is OFF ($S = 0$)

when the switch is ON, the operation equation can be described by (7), however, when the switch is OFF it will be described by (8).

$$\frac{dI_L}{dt} = \frac{1}{L}V_{pv} - \frac{1}{L}V_C, \frac{dV_c}{dt} = \frac{1}{c}I_L - \frac{1}{CR}V_c \tag{7}$$

$$\frac{dI_L}{dt} = \frac{1}{L}V_{pv}, \frac{dV_c}{dt} = \frac{1}{CR}V_c \tag{8}$$

where:
L, C, R: Represent the Inductance, Capacitance and Resistance load of the boost converter respectively. Choosing the state vector as $x(t) = [I_L\ V_c]$ where V_c is the capacitor voltage; I_L is the inductor current. Considering that the controlled output of the system corresponds to the inductor current. The general equation that governs the operation of the boost converter is:

$$\begin{cases} \dot{X}(t) = Ax(t) + BV_{PV}(t) \\ \quad y(t) = Cx(t) \end{cases} \tag{9}$$

where

$$A = \begin{bmatrix} 0 & -\frac{(1-S)}{L} \\ \frac{(1-S)}{C} & -\frac{1}{CR} \end{bmatrix} B = \begin{bmatrix} \frac{1}{L} \\ 0 \end{bmatrix} C = [1 \quad 0]$$

In order to obtain control actions, the variables I_L and V_c can now be predicted for one step horizon. The MPC is to be fed with a discrete time model therefore, it is necessary to compute the converter discrete time model for a given sampling period T_s [35, 36].

Using the forward Euler first order approximation:

$$\frac{dx(t)}{dt} \approx \frac{x(k+1)+x(k)}{T_s} \tag{10}$$

By combining (9) and (10), (11) can be obtained to predict the next value of the Inductor current/Capacitor Voltage.

$$X(k+1) = A_1x(k) + B_1V_{pv}(k) \tag{11}$$

where;

$$A_1 = (I + A.T_s), B_1 = B.T_s$$

T_s : Sampling time
k : Number of iterations
$k+1$: Predicted value

The problem of optimization given in (11) is solved again by using a new set of measured data to determine the new state of the switch, at each sampling time.

3. PROPOSED MPPT METHOD

The MPC principal characteristic is to predic the future behaviour of the control variables over a predefined horizon. In most applications, the load is unknown and time varying. Thus, estimation should be added, which allows the output voltage error limination in the presence of load uncertainties. The reference of output voltage will be adjusted so as to compensate for the deviation of the output voltage from its actual reference. To achieve this, a discrete-time Kalman Filter (KF) is designed.

In this paper, Model predictive control with Kalman Filter scheme based on the output current of Neural Network and estimator current ($NN - MPC - KF$) is introduced for $DC\text{–}DC$ boost converter. Figure 5 shows the hybrid control algorithm. The hybrid model ($NN - MPC - KF$) based $MPPT$ method is proposed in order to predict the behavior of the controlled variables by manipulating the switch state S. The switching state that minimizes the cost function (14) will be selected to be applied at the next sampling time; one-step MPC is applied in this study. In one-step horizon MPC, the variables I_{PV}, V_{PV} and V_c are measured in time k and adopted to estimate the future comportment in time $(k+1)$. The implemented switching state is determined by the optimization of a cost function [37-38].

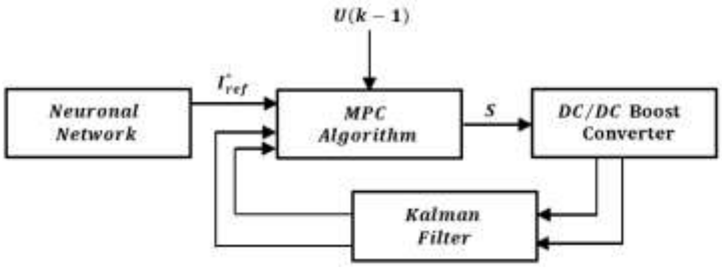


Figure 5. Hybrid control algorithm

3.1. Kalman filter

The Kalman filter is a set of mathematical equations that gives an efcient computational solution of the least-squares method (LSM). The filter is very powerful in several aspects: are used to optimally estimate the variables when they can't be measured directly, also, it can support estimations of past, present, and even future states. In order to find the MPP using this estimator, we need to design this filter to look for the output voltage at the MPP.

The structure of the Kalman filter is given by:

$$\hat{X}(k+1) = A_1 x(k) + B_1 V_{pv}(k) + K\big(y(k) - C\hat{x}(k)\big) \tag{12}$$

The selection principle of the Kalman filter gain is to minimize the error covariance matrix, as follows:

$$K_{i+1} = P_{i+1}\, C_k^T (C_k P_{k+1} C_k^T + R)^{-1} \tag{13}$$

A cost function that helps in obtaining the best control action to be implemented has to be determined. An objective function needs to be chosen that captures the control objectives over the finite prediction horizon. in this study one prediction horizon has been applied, which reduces the number of computations to the number of possible switching states of the converter [39]. The variables used for determining the cost function represented as difference between desired current of PV and predicted values .

The control action can be solved by minimizing a cost function g:

$$g = I_L(k+1) - I^*_{ref} \tag{14}$$

where
K : is the optimal gain vector
g : is the cost function
I^*_{ref} : is the current reference
$I_L(k+1)$: is the predictive current derived from discrete-time model

3.2. Artificial neural network for MPP current estimator

Artificial neural network (ANN) is used in this study in order to approximate the current at MPP of PV system in different conditions. An Artificial neural network (ANN) is a computational model inspires by the biological neural network, it have three layers- input layer, one or more hidden layers and output layer. The input layer receives different information which analyzes in hidden layer, then the results provide by the output layer at the end of analyzed [40-42].

In the present paper, the ANN has been employed for the development of a new MPPT approach. In this technique two stages are achieved to track MPPT of PV array. In the first stage, by the acquisition of the weather parameters "G" (irradiation) and "T" (temperature), which are the inputs of the NN. Then we estimate foe each parameter the optimal power, voltage and current corresponding to the MPP. In the second stage, the optimal current which is the output of the neural network, and the the instantaneous measured current of the PV array is used to generate the switching signals of the DC/DC converter**.** Three-layer of Neural Network is chosen in this study, the two-input layer, which are, the temperature (T) and Irradiance (G) of PV array, 15 neurons in hidden layer and the output layer which is correspond to current I_{mpp}. To train the network input–output datasets were collected using the PV model and varying of different irradiance and cell temperature. To control the output current of PV panel at MPP, the reference signal of MPC is considered as I^*_{ref}.

The different steps of MPC control are as follows:

Step 1: Mesures $V_{pv}(k), I_L(k), I_{ref}^{*}, V_c(k)$

Step 2: Calcute current prediction estimator using Kalman Filter

Step 3: Cost function g evaluation

Step 4: Swiching state selection

Step 6: Apply swiching state

4. RESULTS AND DISCUSSIONS

To evaluate the feasibility and also the performance of the proposed control for tracking the MPP, the system in Figure 1 is implemented by using Matlab/Simulink. The Neural Netwok block delivers the optimal current reference, which is compared to the instantaneous measured current to get minimized au cost function of MPC , then delivers the switching signals of the DC/DC Boost converter.

The analytical model of PV panel which parameters values are listed in Table 1. The PV system includes two modules connected in series and two others connected in parallel.

Table 1. Solar panel specifications

Electrical parameters of the PV system	Value
Maximum power (MP)	110 W
Open circuit voltage (Voc)	43.5V
Short circuit current (Isc)	3.45 A
PV output voltage at MPP	35 V
PV output current at MPP	3.15 A
Number of cells connected in series (Ns)	72
Neural Network performance	Value
Number of inputs (T, G)	02
Number of hidden neurons	15
Testing error (ms)	0.001

To illustrate the benefits from the proposed control technique, different approaches are examined under solar irradiance variations. Based on the mathematical model and environmental Irradiance changes, the power, voltage and current at MPP are also calculated. In proposed hybrid $MPPT$ approach, the current reference I_{PV}^{*} is obtained by Artificial Neural Network. Boost converter is controlled by MPC with parameters fixed as: $C = 1000\ \mu F, L = 15\ mH$ and $R = 30\ \Omega$. Note that the one-step of MPC is adopted in the following simulations. As mentioned earlier, it is necessary to obtain some data as input and output variable to train the Neural Network.

In our work, the inputs to the ANN are Temperature (T), and Irradiance (G) and the output is the current at the MPP, I_{MPP}. The variations of Irradiance and Temperature are very nonlinear in producing the output power, we decided to use Levenberg-Marquardt algorithm to train the Neural Network. The set of data employed to train ANNs has been selected to cover the entire region where the PV system are ordinary to operate. For a given Irradiation and cell Temperature, a PV power and voltage corresponding values are obtained from the mathematical model. From each value of voltage and power, the current value is identified. A total 601 couples of data were used in the training procedure of theANN; 80% of the data was devoted for training and 10% for testing and 10% for validation. Back-propagation training algorithm was used for the training the Network with Levenberg-Marquardt algorithm. The results for ten (10) testing patterns are presented in Table 2.

Table 2. Summary of simulation results

Irradiation G, W/m2	P_{MPP}	V_{MPP}	I_{MPP} From model	I_{MPP} From NN	Error
1000	440	70.64	6.228	6.225	0.003
900	393.6	70.64	5.571	5.566	0.005
710	304.9	70.64	2.919	4.316	0.000
500	20.6.2	70.64	3.589	2.933	0.014
600	253.3	70.64	1.723	3.591	0.005
400	160.7	68.64	2.341	2.275	0.066
200	69.65	64.66	1.076	1.063	0.012

For studying the MPPT technique performance, the PV array is exposed to illumination varying irradiance as show in Figure 6 and the temperature was set to 25°C. As it can be seen , it includes several increasing and decreasing steps which makes it possible to verify the performance of the system in different conditions.

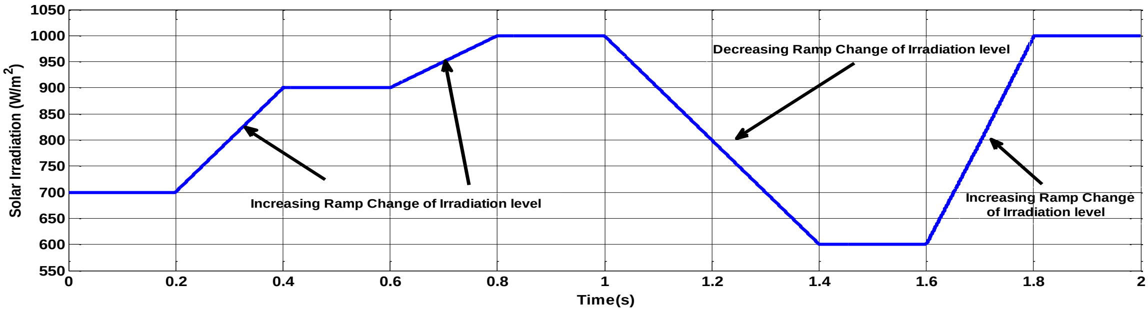


Figure 6. Solar irradiation waveform

The MPC algorithm controller with the sampling time is taken 45µs and the output of Neural Network is current (I_{MPP}). Regarding the Kalman filter (KF), the covariance matrices are chosen as $Q = diag(0.1, 0.1)$ and $R = diag(1, 1)$. The dynamic responses for current of the PV array are illustrated in Figure 7. At the beginning, the irradiance level is set to 700 W/m^2(Fig 6). The proposed MPPT ($NN - MPC - KF$) algorithm reaches the MPP at $t = 21.7ms$ whereas when using others algorithms takes more time; it takes $33.7ms$ for conventional $P\&O$ algorithm, $24.9ms$ for $NN - PI$ algorithm and $22.71ms$ for NN-MPC algorithm. However the PV power is oscillating around the MPP (295.5–300.5W, 295-301W; 299.9-300.35W, 299.9-300.3W) for Conventional $P\&O$, $NN - PI$, $NN - MPC$ and the proposed MPPT. The proposed method can reach the new MPP faster in case of sudden change in solar irradiance; the output powers oscillations are almost neglected.

Figure 7 shows the waveforms of reference current generated by the proposed hybrid $MPPT$, $NN - MPC$, $NN - PI$ and also $P\&O$ algorithms. In order to evaluate the dynamic performance of the above-mentioned algorithms, the waveforms of reference current are magnified around $t = 0.5s$, $t = 1.1s$ (decreasing ramp) and $t = 1.7s$ (increasing ramp) and shown in the same figure.

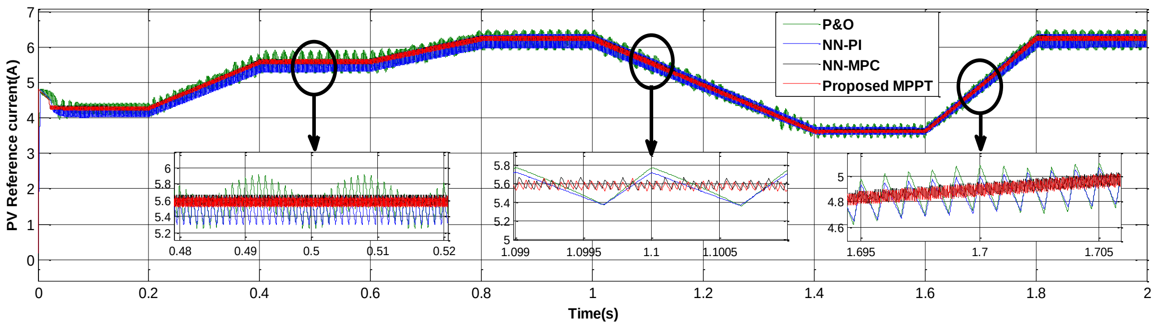


Figure 7. PV Current curves for different MPPT algorithms during different fluctuation in solar radiation

As obviously seen from Figure 7, Conventional $P\&O$ and $NN - PI$ show a lot of oscillation compared to the the proposed hybrid method. Whereas NN based MPC ($NN - MPC$) has approximately the same performance as the proposed MPPT. The traking speed and oscillations magnitude of the proposed hybrid $MPPT$, $NN - MPC$ and $P\&O$ algorithms are compared in Table 3 where we can constate the superiority of the proposed MPPT comparatively to the algorithms mentioned above.

As it can be seen in Table 3, their oscillation is high comparing with the proposed MPPT algorithm; in which we can observe a huge improvement obtained with the hybrid MPPT method proposed.

Table 3. Results comparison between the proposed method and other algorithms

MPPT Algorithms	Irradiance 700 W/m²		Irradiance 900 W/m²		Irradiance 1000 W/m²		Irradiance 600 W/m²		Irradiance 1000 W/m²	
	Traking Speed time (ms)	Power Oscillation (w)	Traking Speed time (ms)	Power Oscillation (w)	Traking Speed time (ms)	Power Oscillation (w)	Traking Speed time (ms)	Power Oscillation (w)	Traking Speed time (ms)	Power Oscillation (w)
P&O	22	18	4.5	18.32	4	12.5	2	5.5	5	12.5
NN-PI	28	3	3	2.80	3	2.1	1	1.3	3	1.8
NN-MPC	21	0.40	3	0.45	2	0.56	1	0.56	3	0.59
Proposed MPPT	19	0.35	3	0.36	2	0.45	1	0.40	2	0.56

Figure 8 shows the output power and as it can be seen $P\&O$, $NN-PI$ and $NN-MPC$ algorithms show more oscillation compared to the proposed $MPPT$ method. It can be observed that the output power obtained in four steps of irradiation, demonstrates clearly that the four methods $P\&O$, $NN-PI$, $NN-MPC$ and the proposed hybrid MPPT guarantee the maximum power. The overshoot of output power for four $MPPT$ methods is presented also in the same figure, in which it can be observed a great improvement obtained with $NN-MPC$ and the proposed hybrid MPPT methods. Table 4 shows MPPT perfomances comparison. Figure 9 shows a comparative study between hybrid proposed MPPT and Neural Network-Model under four irradiation changes.

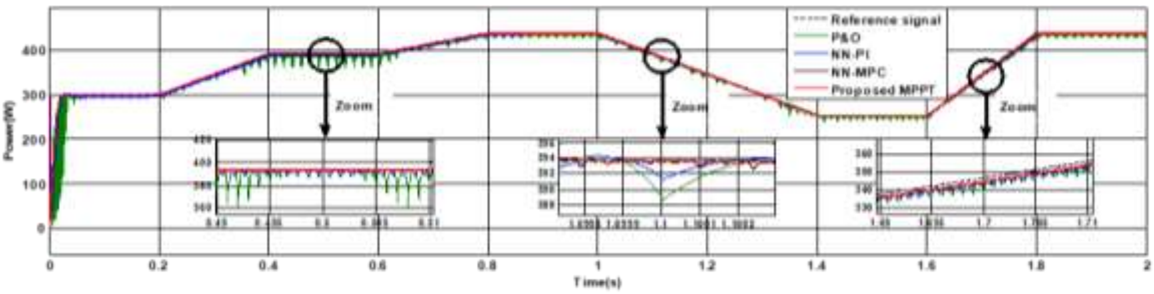


Figure 8. Output power for different MPPT algorithms under different irradiation changes

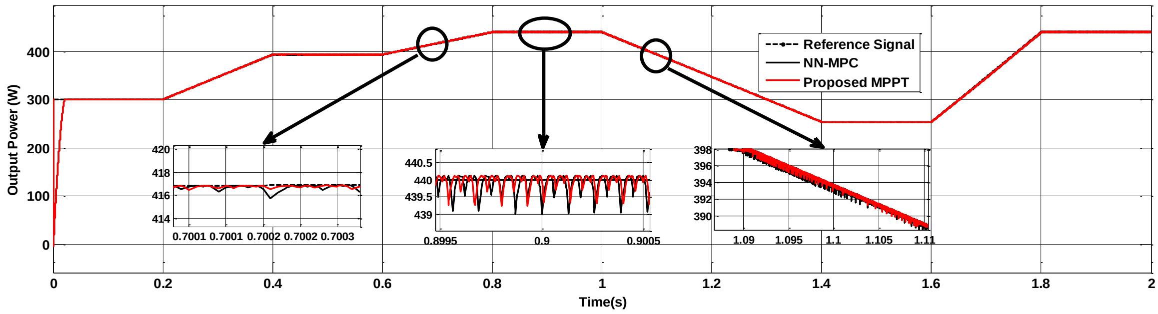


Figure 9. Output voltage for Hybrid proposed MPPT and NN-MPC under four irradiation changes

Table 4 shows the output power efficiency and accuracy obtained in four steps of irradiation by the proposed MPPT, $NN-PI$, $NN-MPC$ and $P\&O$ algorithms. The efficiency is calculated using the maximum theoretical power and the instantaneous extracted power defined as:

$$E(\%) = \left(\frac{P_{MPPT}}{P_{Max}}\right) \times 100 \tag{16}$$

where:
P_{MPPT} : is the PV array output power.
P_{Max} : is its theoretical maximum power.

Table 4. Accuracy and Efficiency of the different MPPT

MPPT Algorithms	Step increase in irradiance 700→900 W/m²		Step increase in irradiance 900→1000 W/m²		Step increase in irradiance 1000→600 W/m²		Step increase in irradiance 600→1000 W/m²	
	Traking Accuracy	Power Effeciency	Traking Accuracy	Power Effeciency	Traking Accuracy	Power Effeciency	Traking Accuracy	Power Effeciency
P&O	Bad	98.77%	Moderate	98.92%	Bad	98.81%	Moderate	98.34%
NN-PI	Bad	99.39%	Bad	99.61%	Moderate	99.88%	Moderate	99.26%
NN-MPC	Good	99.94%	Good	99.89%	Good	99.90%	Good	99.49%
Proposed MPPT	Good	99.96%	Good	99.90%	Good	99.90%	Good	99.51%

From Table 4, it can be observed that the output power obtained in four irradiation steps, demonstrates clearly that the four methods: Conventional $P\&O$, $NN-PI$, $NN-MPC$ and proposed hybrid $MPPT$ guarantee the maximum power point (MPP) efficiency in the four irradiation steps, however, proposed MPPT reduce oscillation around the MPP compared to Conventional $P\&O$, Neural Network based PI and Neural Network based MPC (see table 3).

5. CONCLUSION

In this paper, new hybrid MPPT controller combining Neural Network-Model Predictive-Kalman Filter ($NN-MPC-KF$) techniques have been presented. The neural networks inputs are irradiance level and temperature. The optimal current of the PV is the output of the ANN. Moreover, a predictive controller (MPC) is used to improve boost converter efficiency and Kalman Filter is used to estimate the converter state vector for minimizes the cost function then predict the future value to track the Maximum Power Point (MPP) with fast changing weather parameters.

Simulation results have been presented under several atmospheric conditions, in which many indexes perfomances have been studied. According to the obtained results, we can conclude that the proposed hybrid MPPT method gives better performance of compared to Conventional P&O, Neural Network based PI controller and Neural Network based Model Predictive control methods especialy in term of low ripple and low overshoot. The simulation results have revealed also that the proposed MPPT algorithm exhibits better output power, medium oscillation around the MPP point under the steady state condition and no divergence from the MPP during varying weather conditions regardless of the speed of change. It has been shown in results that the proposed MPPT method under different irradiance conditions can track the MPP in a fast way and more efficient in compared to other methods. The future work of this study will be the implementation of the proposed method in a real hardware device.

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